

## DTC-ANN-2-level hybrid by neuronal hysteresis with mechanical sensorless induction motor drive using KUBOTA observer

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### ABSTRACT

In this paper, DTC is applied for two-level inverter fed IM drives based on neuronal hysteresis comparators and The Direct Torque Control (DTC) is known to produce quick and robust response in AC drive system. However, during steady state, torque, flux and current ripple. An improvement of electric drive system can be obtained using a DTC method based on ANNs which reduces the torque and flux ripples, the estimated the rotor speed using the KUBOTA observer method based on measurements of electrical quantities of the motor. The validity of the proposed methods is confirmed by the simulation results. The THD (Total Harmonic Distortion) of stator current, torque ripple and stator flux ripple are determined and compared with conventional DTC control scheme using Matlab/Simulink environment.

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## 1. INTRODUCTION

The direct torque control methods of asynchronous machines appeared in the second half of the 1980s as competitive with conventional methods, based on pulse width modulation (PWM) power supply and on a splitting of flux and motor torque by magnetic field orientation. Indeed, the DTC command from external references, such as torque and flux, does not search, as in conventional commands (vector or scalar) the voltages to be applied to the machine, but search "the best" state of switching of the inverter to meet the requirements of the user [1]. The design of artificial intelligence was developed in the early 1960s. It includes methods, tools and systems to solve the problems that normally require the intelligence of man [2]. The term intelligence is always defined as the ability to learn in an effective way, to react in an adaptive way, to make the right decisions in a sophisticated way and to understand phenomena [3]. Artificial intelligence-based speed controls (Neural network and fuzzy logic) that do not require knowledge of a mathematical model have recently been proposed. [4]. Fuzzy logic controllers are ideal candidates for controlling such systems, unfortunately there are no precise methods for determining the tuning strategy. The latter must be built by trial and error using the tests on the system to be adjusted [5]. On the other hand, these approaches have good robustness to parametric variations and measurement noises, their computing conditions, the elaboration time and the need for expert knowledge of the system, limit current applications to a limited range and sometimes very specific [6].

In recent years ANNs have gained a wide attention in control applications. For that, we developed an intelligent technique to improve the dynamic performances of the DTC. This method consists in replacing the traditional ST applied to the IM- DTC by an ANNs [7].

Major disadvantage of DTC is the ripple on the couple and the flux and to remedy this last problem one improves the control DTC by several techniques among these methods are modification the tables of selection, the artificial intelligences which is interested in this article and the flux is estimated by the KUBOTA observer.

In this work, our main objective is to exploit artificial intelligence tools namely, networks of artificial neurons on the DTC control, artificial neural networks on the DTC control DTC-ANN, we use the adaptive observer of KUBOTA to estimate the flux, and we express the estimation error then THD of stator current is evaluated.

The modelling is presented in Matlab/Simulink models in order to study the performance of the drive system under steady state and dynamic conditions during starting, and speed reversal and load perturbations. The simulation results show that the proposed control method can achieve very robust and satisfactory performance.

## 2. CONVENTIONAL DTC

Depenbrock and I. Takahashi proposed DTC control of the asynchronous machine in the mid-1980s, it has become increasingly popular. The DTC control makes it possible to calculate the control quantities that are the stator flux and the electromagnetic torque from the only quantities related to the stator and this without the intervention of mechanical sensors [8].

The principle of control is to maintain the stator flux in a range. The block diagram of the DTC control is shown in Figure 1.

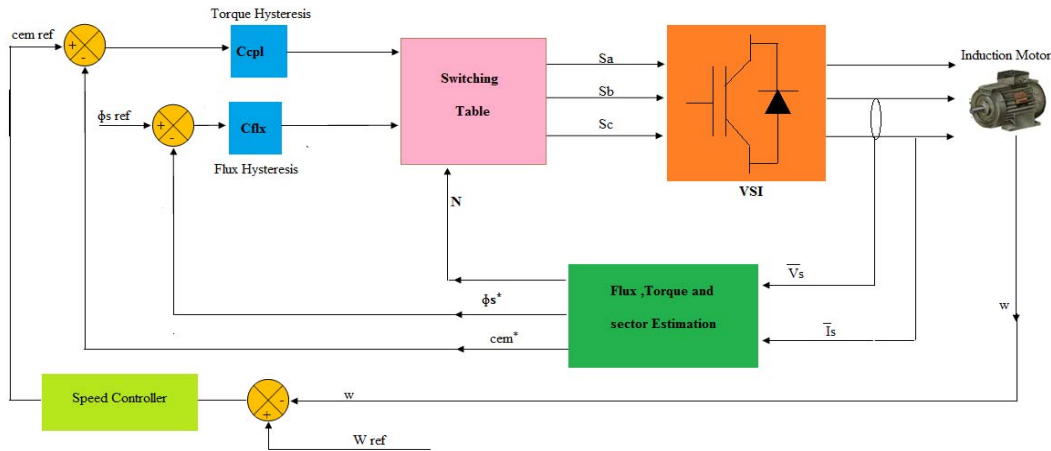


Figure 1. Structure of conventional DTC.

This strategy is based generally on the use of hysteresis comparators whose role is to control the amplitudes of the stator flux and the electromagnetic torque: [9]

$$\begin{cases} \Phi_{s\alpha} = \int_0^t (v_{s\alpha} - R_s i_{s\alpha}) dt \\ \Phi_{s\beta} = \int_0^t (v_{s\beta} - R_s i_{s\beta}) dt \end{cases} \quad (1)$$

$$T_e = \frac{3}{2} P [\Phi_{s\alpha} i_{s\beta} - \Phi_{s\beta} i_{s\alpha}] \quad (2)$$

The DTC control method allows direct and independent electromagnetic torque and flux control, selecting an optimal switching vector.

The Figure.2 shows the schematic of the basic functional blocks used to implement the DTC of induction motor drive. A voltage source inverter (VSI) supplies the motor and it is possible to control directly the stator flux and the electromagnetic torque by the selection of optimum inverter switching modes [10].

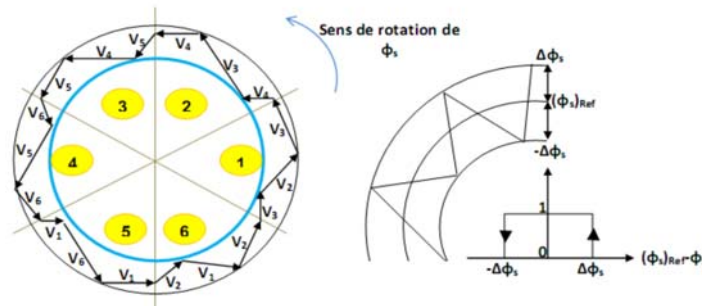


Figure 2. Voltage vectors

The switching table allows to select the appropriate inverter switching state according to the state of hysteresis comparators of flux (cflx) and torque (ccpl) and the sector where is the stator vector flux ( $\phi_s$ ) in the plan ( $\alpha, \beta$ ), in order to maintain the magnitude of stator flux and electromagnetic torque inside the hysteresis bands.

The above consideration allows construction of the switching table [11], is given in Table 1.

Table 1. The selection of electrical tention

	N	1	2	3	4	5	6
Cflx	Ccpl						
1	1	2	3	4	5	6	1
	0	7	0	7	0	7	0
	-1	6	1	2	3	4	5
0	1	3	4	5	6	1	2
	0	0	7	0	7	0	7
	-1	5	6	1	2	3	4

### 3. DTC WITH ARTIFICIAL NEURONAL NETWORK (DTC-ANN)

Conventional DTC control has several disadvantages, such as obtaining a variable switching frequency, torque and flux ripples, power fluctuations, and harmonic currents in the transient and steady state, because of the use of hysteresis comparators and switching tables. For this, we proposed to study in this part the direct control of the pair based on artificial neural networks, to improve the performance of the DTC commands, where the conventional comparators and the switching table are replaced by a neural controller, so to drive the output quantities of the MAS to their reference values for a fixed period of time. Numerical simulations are presented to test the performances of the proposed methods (DTC-ANN), is represented by Figure 3. [12].

The structure of the direct neural control of the torque (DTC-ANN-2N), of the asynchronous machine powered by two-level NPC inverter, is represented by Fig.3.

The update of the weights and Bias of this network is carried out by a retro-propagation algorithm called the Levenberg-Marquardt (LM) algorithm [13].

The choice of neural network architecture is based on the mean squared error (MSE) obtained during learning [14]. The following figure shows the structure of neural networks for two-level neuronal Design of KUBOTA observer.

The block diagram of the DTC-ANN control is shown in Figure 3.

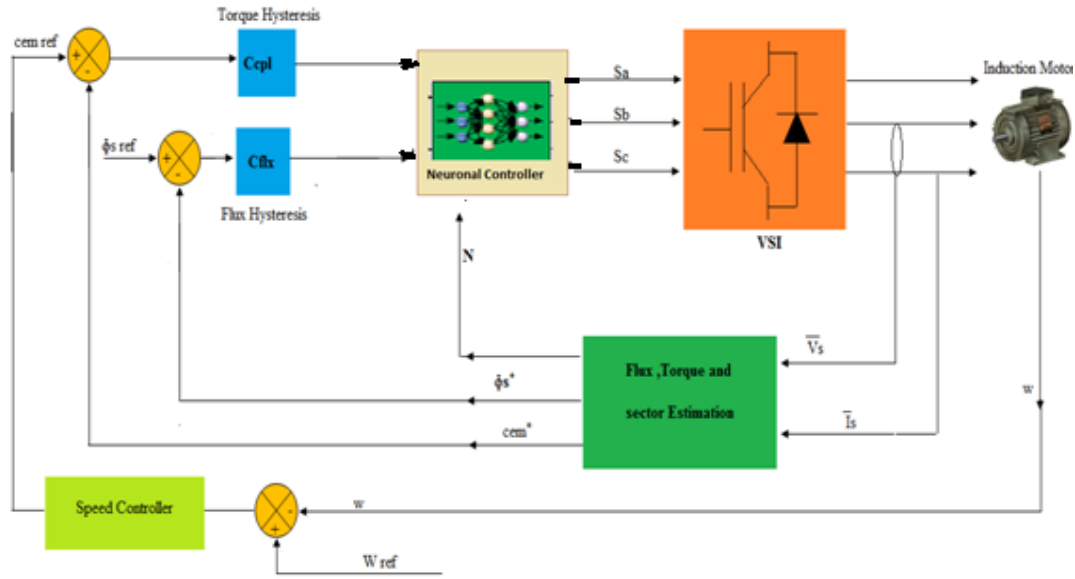


Figure .3 DTC-ANN

#### 4. DESIGN OF HYSTERESIS NEURONAL COMPARATORS WITH KUBOTA OBSERVER

Neural networks are mathematical models inspired by the brain's functioning of the human being. Their faculty of learning, generalization and approximation, make two new solutions for the modelling, identification and control of processes by their ability to process input-output data of the system [15]. The choice of a neural network to improve the performance of the proposed DTC control is obtained after several simulation tests.

The principle of neural networks DTC with KUBOTA observer is similar to traditional DTC control. The difference is using a neural networks controller to replace the torque and flux hysteresis loop controller, and using KUBOTA observer for observing speed of induction motor. [16],[17].

The hysteresis comparators is replaced by a perceptron neuron network, comprising a 1 neuron input layer, a four neuron hidden layer, and a 1 neuron output layer. The activation functions are of tansig forms for the input layer and purelin for the hidden layer neuron, and trainlm for the output layer neuron is illustrated in Figure 4. [17].

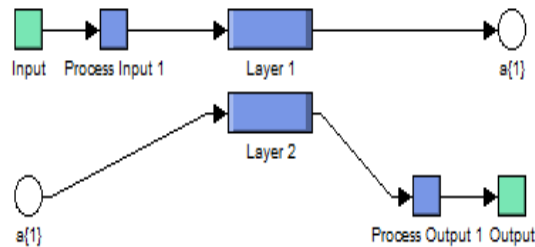


Figure .4 Architecture of the neural hysteresis controller of torque and flux.

#### 5. THE OBSERVATION

The estimators used in open loop, based on the use of a copy of a model representation of the machine. This approach led to the implementation of simple and fast algorithms, but sensitive to modelling errors and parameter variations during operation [18].

Is an estimator operating in a closed loop and having an independent system dynamics. It estimates an internal physical quantity of a given system, based only on information about the inputs and outputs of the

physical system with the feedback input of the error between estimated outputs and actual outputs, using the K matrix gain to thereby adjust the dynamic convergence error [19] as shown in Figure 5.

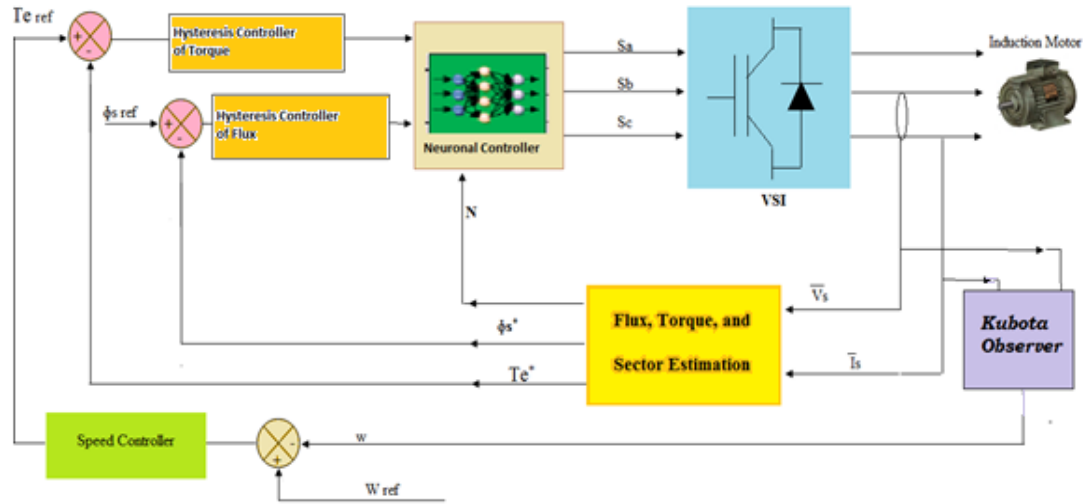


Figure .5 DTC-ANN associated with the KUBOTA observer.

### 5.1. Representation of the KUBOTA Observer

The structure of the KUBOTA Adaptive Observer is illustrated in Figure 6. [19], [20], [21]. When the rotation speed of the MAS is not measured, it is considered as an unknown parameter in the observer equation system based on the vector state model of the induction machine described in the stator frame and having as state vector.

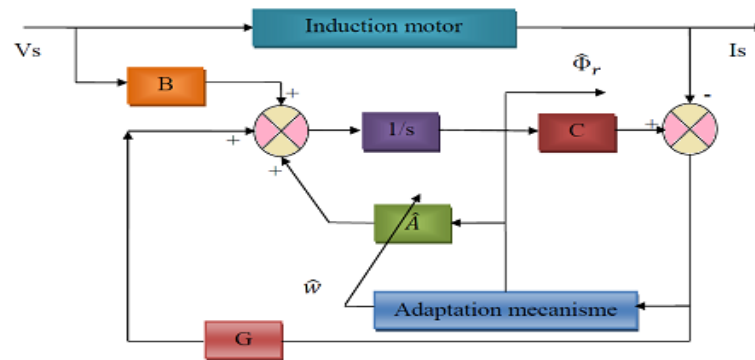


Figure 6. The Observer of KUBOTA.

### 5.2. The Modelling of the Observer of KUBOTA

#### 5.2.1.State model

$$\begin{cases} \dot{x} = Ax + Bu \\ y = Cx \end{cases}$$

(3)

$$[A] = \begin{bmatrix} .A11 & .A12 \\ .A21 & .A22 \end{bmatrix} \quad x = \begin{bmatrix} I_s \\ \phi_r \end{bmatrix}$$

with:

So the observatory associated with this model is written as:

$$\frac{d\tilde{x}}{dt} = \tilde{A}\tilde{x} + B_{us} + G(I_s - \tilde{I}_s) \quad (4)$$

$$G = \begin{bmatrix} g_1 & g_2 & g_3 & g_4 \\ -g_2 & g_1 & -g_4 & g_3 \end{bmatrix}^T$$

With:

By asking that  $e = x - \tilde{x}$  estimation error between the model and the observer.

$$\frac{de}{dt} = (A - GC)e - \Delta\tilde{x} \quad (5)$$

### 5.2.2. Adaptation mechanism

The speed adjustment mechanism is derived from the application of LYAPUNOV theorem on system stability. Let LYAPUNOV function defined positive [22]:

$$V = e^T e + \frac{(w - \tilde{w})^2}{\lambda} \quad (6)$$

Otherwise, the derivative of this function with respect to time is negative:

$$\frac{dV}{dt} = e^T Q e - 2\Delta w \left[ k(e_{is\alpha} \tilde{\phi}_r \beta - e_{is\beta} \tilde{\phi}_r \alpha - \frac{d\tilde{w}}{\lambda dt}) \right] \quad (7)$$

With:  $e_{is\alpha} = i_s \alpha - \tilde{i}_s \alpha$ ,  $e_{is\beta} = i_s \beta - \tilde{i}_s \beta$

$$Q = (A - GC)^T + (A - GC) \quad (8)$$

Equation (8) must be set negative according to the LYAPUNOV stability theory. Therefore, by careful selection of the gain matrix G, the matrix Q must be a negative definite matrix and the adaptation mechanism for estimating the speed will be reduced by cancellation of the 2<sup>nd</sup> term of the equation (9)[23].

The estimate of the speed is done by the following law :

$$\tilde{\omega} = k\lambda \cdot (e_{is\alpha} \tilde{\phi}_r \beta - e_{is\beta} \tilde{\phi}_r \alpha) dt \quad (9)$$

To improve the speed of dynamic observation, propose to use PI instead of a pure integrator [24]:

$$\tilde{\omega} = k_p \cdot (e_{is\alpha} \tilde{\phi}_r \beta - e_{is\beta} \tilde{\phi}_r \alpha) + k_i \int (e_{is\alpha} \tilde{\phi}_r \beta - e_{is\beta} \tilde{\phi}_r \alpha) dt \quad (10)$$

## 6. SIMULATION RESULTS AND ANALYSIS

The direct torque control applied to an induction machine is simulated under the Matlab/ Simulink environment. The simulation is performed under the same conditions, Result shown in Figures (From 7 to 13).

### 6.1. Comparative study between DTC and DTC-hysteresis comparators

The DTC and the DTC-ANN applied to an induction machine is simulated under the Matlab/Simulink environment. The simulation is performed under the same conditions. Result shown in Figures (7 to 9) the torque, the speed and the flux.

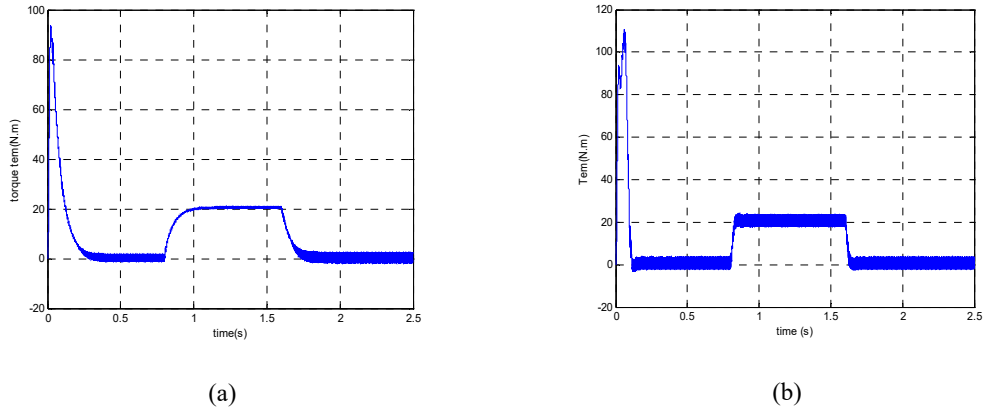


Figure 7. Torque responses, a) Classical DTC control, b) DTC with neural hysteresis comparators

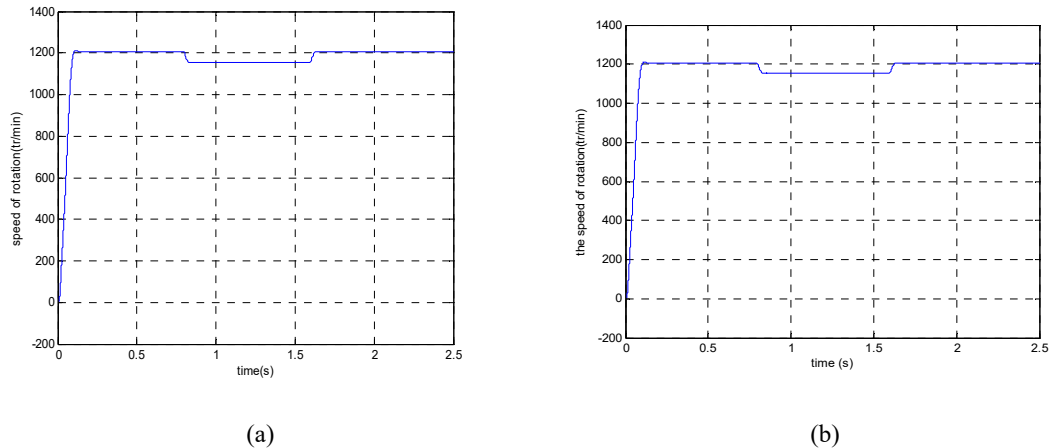


Figure .8 Speed responses. a) Classical DTC control, b) DTC with neural hysteresis comparators

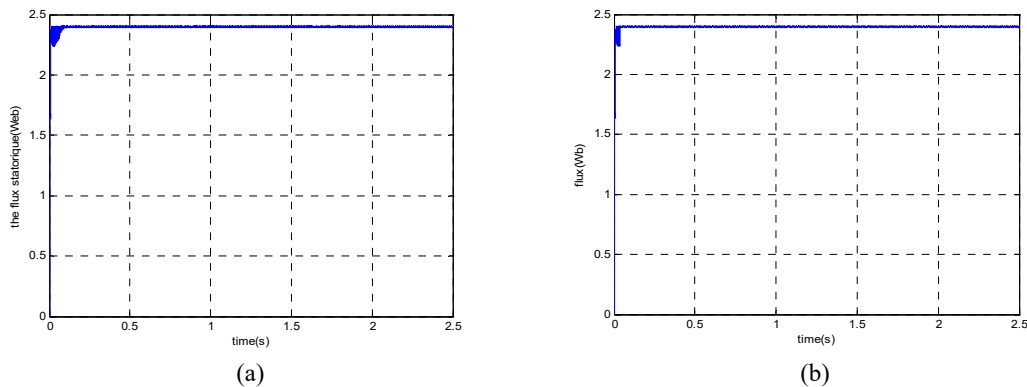


Figure .9 The stator flux. a) Classical DTC control, b) DTC with neural hysteresis comparators

### 6.2. Control DTC-ANN sensorless (KUBOTA Observer) to estimate the speed and the flux

Result shown in Figure 10 to estimate the speed, estimate the flux and evaluation of the error estimation.

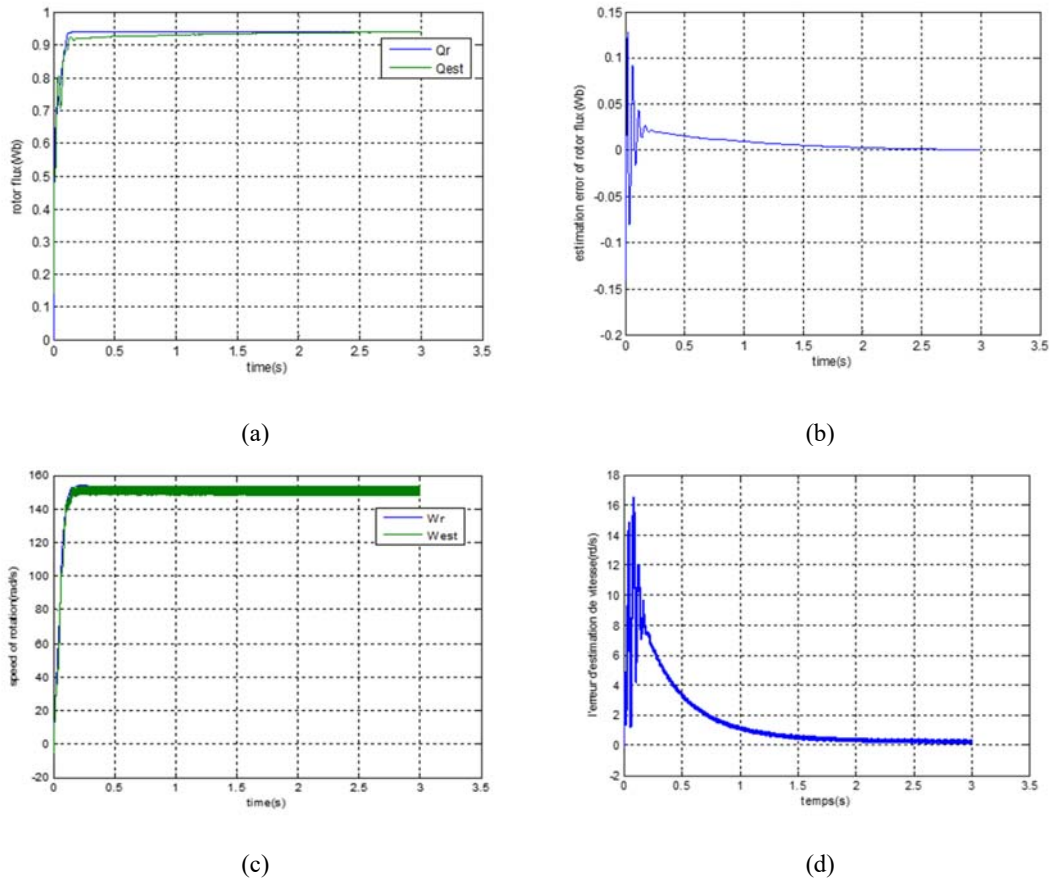


Figure 10. DTC-ANN control with KUBOTA, a) The estimation of the flux, b) Estimation error of flux, c) The estimation of the speed, d) Estimation error of speed

### 6.3. Test of the robustness in low speed of the KUBOTA observer

Result shown in Figure 11 test of the low speed.

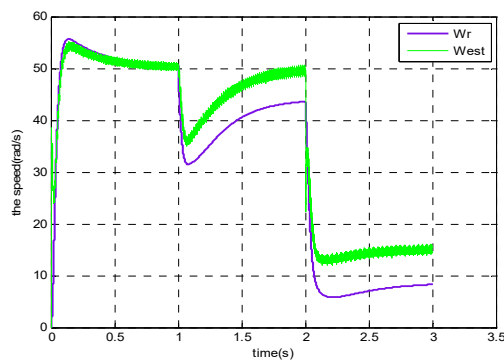


Figure .11 Testing in low speed ( $\approx 10$ Rad/s)



#### 6.4. THD of the current stator (DTC, DTC-ANN)

Result shown in Figures (12 to 13) the THD of the current stator (DTC and DTC-ANN).

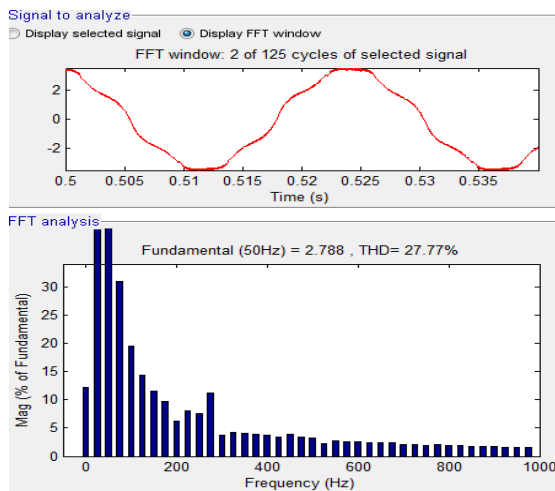


Figure .12 THD value of classical DTC

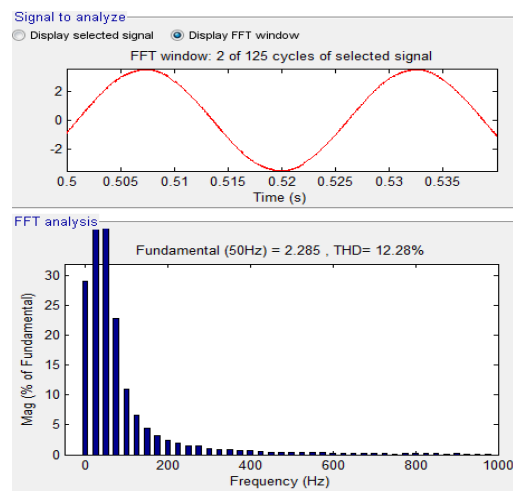


Figure .13 THD value of DTC-ANN

#### 6.5. Analysis and discussion

The figures show that the simulation results using artificial intelligence techniques (neural hysteresis) and DTC-ANN show that the tracking of the set point is perfect. We note that the ripple of electromagnetic torque and stator flux reduces perfectly compared to conventional DTC without neural hysteresis comparator. It is more apparent through the trajectory of the stator flux. In addition to a large decrease in THD as shown in the table above, we were able to conclude that the DTC control by neural hysteresis showed good performance than the classical DTC control but the DTC-ANN is most excellent.

These results prove that our sensorless control with adaptation of is insensitive to the variations of the stator resistances. It is also noticed that the observer corrects well the rotor flux (the square of the rotor flux) and the speed of rotation, since the estimated quantities follow an acceptable way the actual magnitudes of the machine, hence a tracking error is almost zero between the two sizes. This implies a stable observation. But we have a problem of the ripples, especially for the observer of KUBOTA.

Simulation results show that using the observer is important in the control of the machine, the estimation error as zero in the steady state. The major advantage for KUBOTA observation technique is its insensitivity to the machine settings and its responding to low speeds that are near to 10 Rad/s. This proves its robustness.

To reduce the burden of PI tuning and to enhance the drive performance at low speed region, adaptive PI controller in MRAS is replaced by artificial intelligent Neuro fuzzy controller. An exhaustive analysis is carried out with MRAS observer with rotor flux and reactive power schemes with PI and NFC as adaptive controllers and simulation results are compared and shown in papers [24, 13].

Table 2 shows that the simulation results using artificial intelligence techniques (neural hysteresis) show that the tracking of the set point is perfect. We note that the ripple of electromagnetic torque and stator flux reduces perfectly compared to conventional DTC without neural hysteresis comparator. It is more apparent through the trajectory of the stator flux. In addition to a large decrease in THD as shown in the table above, we were able to conclude that the DTC control by neural hysteresis showed good performance than the classical DTC control, compared to the papers [22, 25]. Detail is shown in Table 2.

Table 2. The performances of KUBOTA observer

	Precision	swiftness	Oscillation	Low speed
DTC-ANN with KUBOTA observer	More accurate	Fast below	Missing	Excellent $\approx 10 \text{ Rad/s}$

Table 3 shows that the simulation results using artificial intelligence techniques (neural hysteresis) show that the tracking of the set point is perfect. Conventional DTC without neural hysteresis comparator it is more apparent through the trajectory of the stator flux in addition to a large decrease in THD as shown in the table above, we were able to conclude that the DTC control by neural hysteresis showed good performance than the classical DTC control.

Table.3 Comparison between the Performances of Conventional DTC and DTC-ANN.

	Minimizations ripples of the torque	Minimizations ripples of the flux	Ias THD (%)
Conventional DTC	Exist	Exist	27.77
DTC – ANN	Few	Few	12.28

## 7. CONCLUSIONS

In this work, we mainly presented the estimation of the rotor flux by the KUBOTA adaptive state observer, then we evaluated the estimation error of the flux, we also devoted to improve the performances of the direct control of the torque of the asynchronous two-level UPS powered machine based on artificial intelligence techniques by DTC-ANN. The simulation results show that the use of both estimators is important in the control of the induction machine, the transient and very short regime and the error between the flux estimated and measured to zero in the steady state, the robustness tests of the estimator are also verified. The observer of KUBOTA also plays its role, and gives good results. We can say the use of the estimator brings a clear improvement to the looped structure. Note that the research work is very few, especially with regard to the observer of KUBOTA so I want to expand further and using different controls.

In order to improve the performance of the DTC (torque ripple reductions, flux, and the THD value of the stator current), simulation tests of the control by variation and inversely of the load torque, were presented, the results obtained show this strategies proposed with the techniques of the artificial intelligence (DTC-ANN and DTC-hysteresis neuronal) are very powerful and robust.

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